# Advances in state estimation for lithium-ion batteries



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## Agenda

- Introduction
- Motivation in "non-consumer" applications
- Battery management systems
- The problem of state estimation
- Principle of particle filters
- Dual particle filter for state of charge and state of health estimation
- Results
- Conclusions

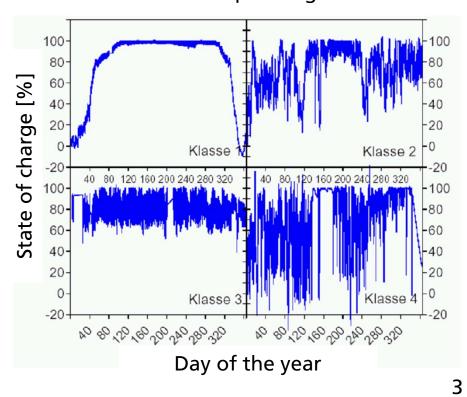




#### **Motivation in non-consumer products**

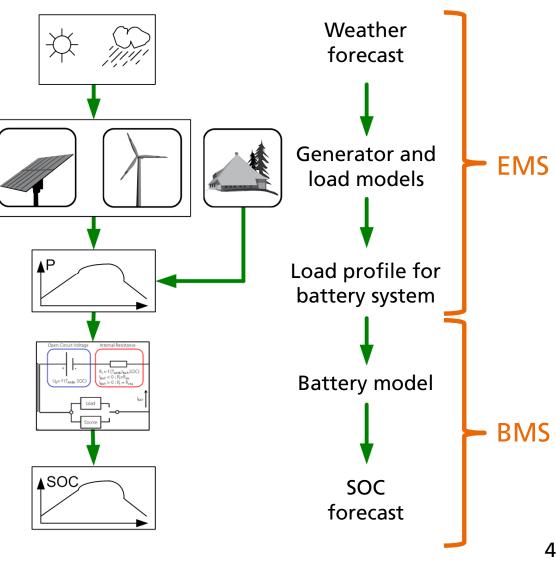
- Fluctuating renewable resources
- Frequently full charging not secured
- Partial cycling at different state of charge levels
- Precise state algorithms necessary for an optimized energy management

Example: Storages in PV off-grid systems Classification of operating conditions



## **Example power supplies: Smart battery management as** part of an optimized energy management

- Communication interface between EMS and BMS
- Model based energy management
  - Load and generation management
  - > Optimized operation of battery system
  - $\rightarrow$  Control of energy fluxes
- Model based battery management
  - SOC prediction in dependence on load profile forecast
  - > Efficiencies in dependence on load profile forecast
  - Information on aging





#### Battery management systems Motivation and objective

#### **Objective:**

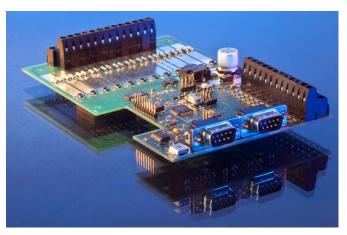
Lithium-ion cells have to be monitored and controlled, important issues are:

- Safety (e.g. overvoltage/undervoltage detection)
- Cycle and calendar life time
- State estimation
- Temperature/voltage monitoring
- High efficiency (well suited cell balancing, low energy consumption of the BMS)

#### **Objective reachable** with high end battery management systems



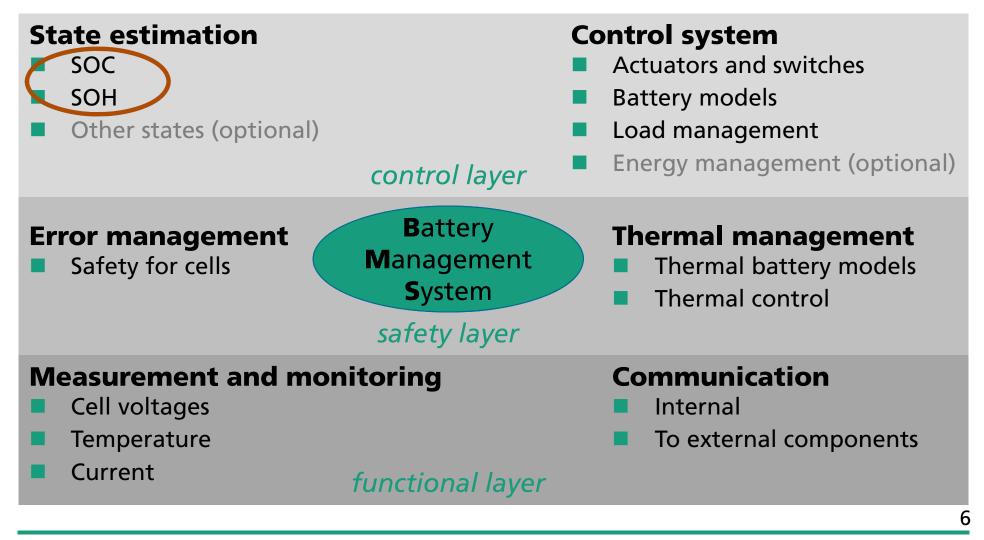
Central management unit



Module management unit 5



#### Battery management system Overview and function blocks





## The problem of state estimation

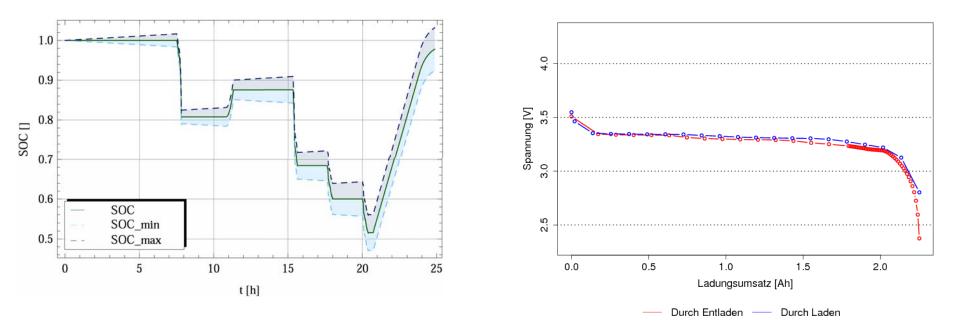
Inner states of the batteries need to be known for e.g.

- Prognosis of the remaining run-time in an application
- Estimations of power capability
- The point in time for replacing the batteries
- Inner states cannot be measured directly:
  - Inner resistance
  - State of charge (SOC)
  - State of health (SOH)
- Procedures shall only use simple measurement values like terminal voltage, current and temperature



#### **Example: State of charge estimation**

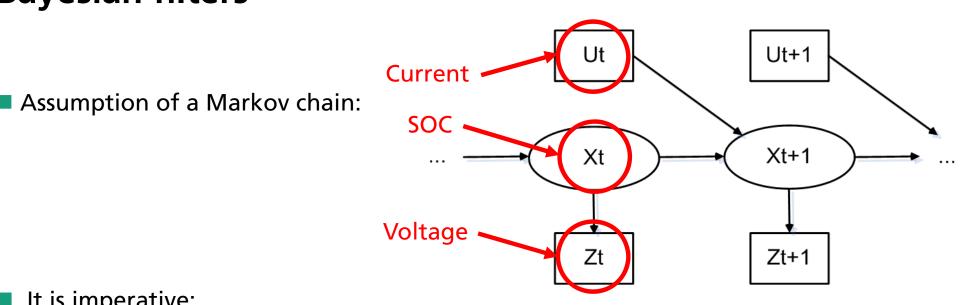
- Ah counter: Integration of measurement errors
- Most conventional approaches:
  - Use of some kind of OCV correction in combination with Ah counting
    - $\rightarrow$  Recalibration of the SOC value via OCV consideration needs resting phases
- Flat OCV characteristic with hysteresis for LiFePO<sub>4</sub>





## Introduction to **Bayesian filters**

#### **Example SOC estimation**



#### It is imperative:

- Input U and Output Z are stochastically independent
- > If  $X_t$  and  $U_t$  are known, then  $X_{t+1}$  will be independent from all previous states  $X_{1}, \dots, X_{t-1}$
- $\succ$  U<sub>t</sub> is statistically independent from  $X_1, \dots, X_t$  and  $U_1, \dots, U_{t-1}$
- > If  $X_t$  is known,  $Z_t$  will be independent from all other variables
- Bayesian filtering equation:  $P(x_t) = \eta^{-1} P(z_t \mid x_t) \int P(x_t \mid x_{t-1}, u_{t-1}) P(x_{t-1}) dx_{t-1}$
- A typical filter of this family is the Kalman filter



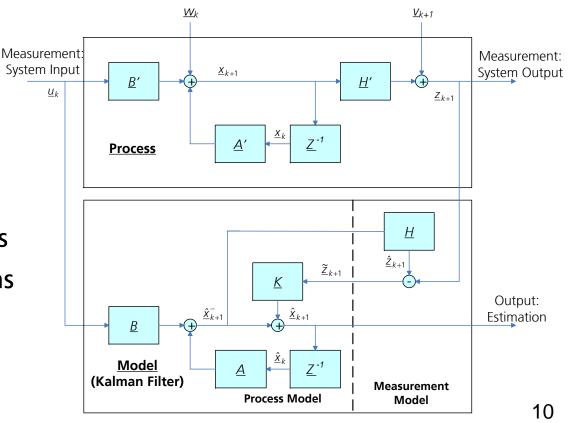
## Kalman filter approach

## **Example: State of charge determination**

- Recursive stochastic state estimator
- More insensitive against measurement errors
- No resting phases necessary for recalibration of SOC
- Fast identification of starting values
- Improved performance for aged batteries

Drawbacks:

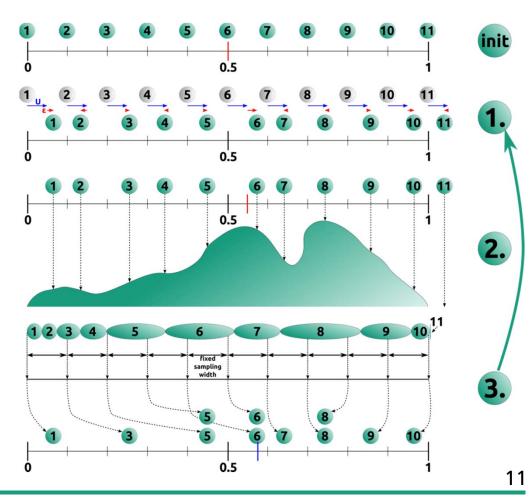
- Optimal estimator only for processes with Gaussian noises
- Suitable only for linear systems
  - $\rightarrow$  For non-linear systems: **Extended or Unscented** Kalman Filter





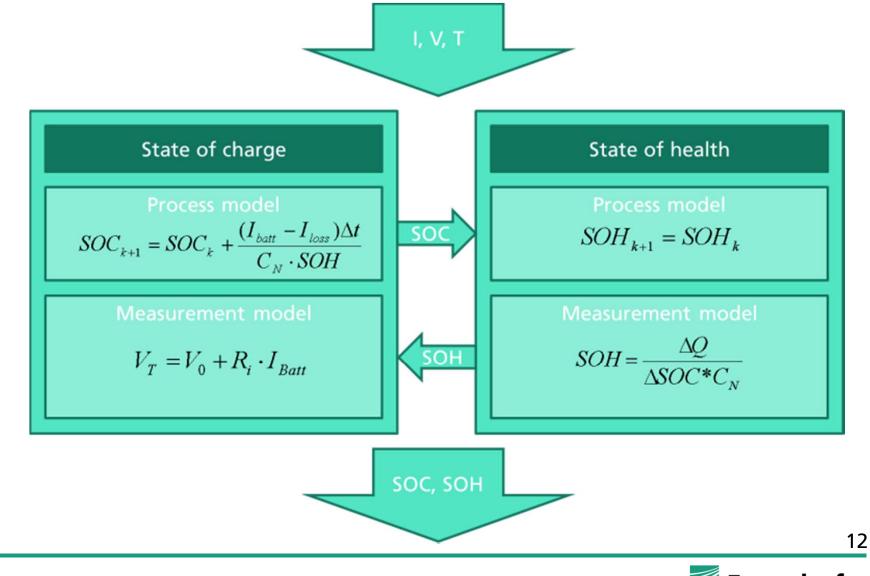
#### Particle filter approach Introduction

- All probability density functions are approximated by samples (Monte Carlo method)
- Offers possibility to deal with any kind of distribution by approximating the respective probability density function by a set of particles or samples
- Offers possibility to use multimodal distributions

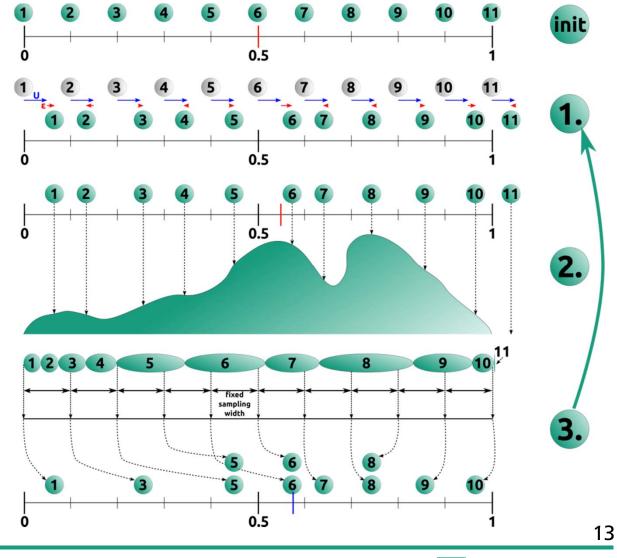




## **Dual particle filter** State of chare and state of health estimation



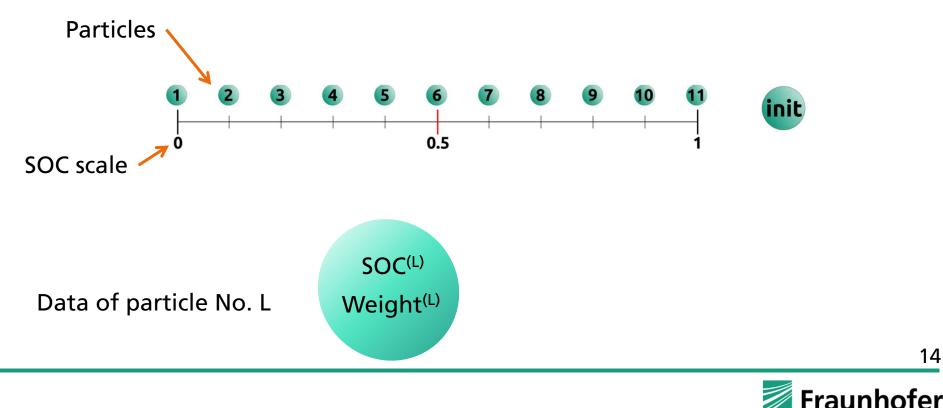




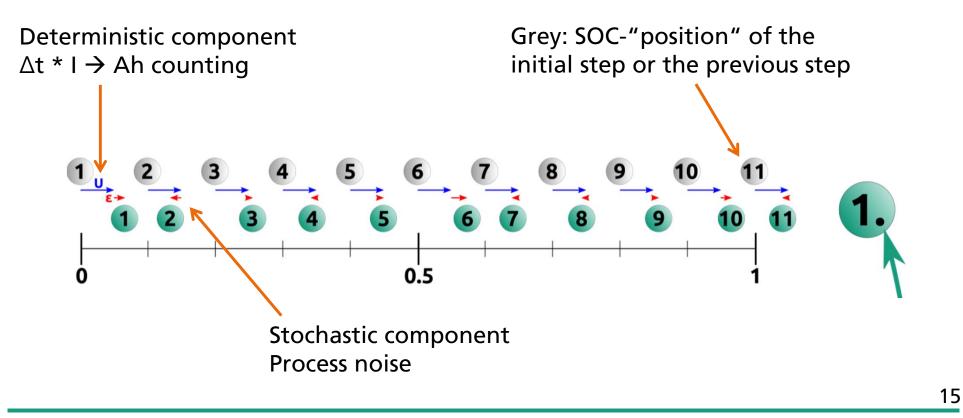


**Initialization:** No preliminary information

- $\rightarrow$  SOC unknown
- $\rightarrow$  Particles have been uniformly distributed over the entire SOC scale

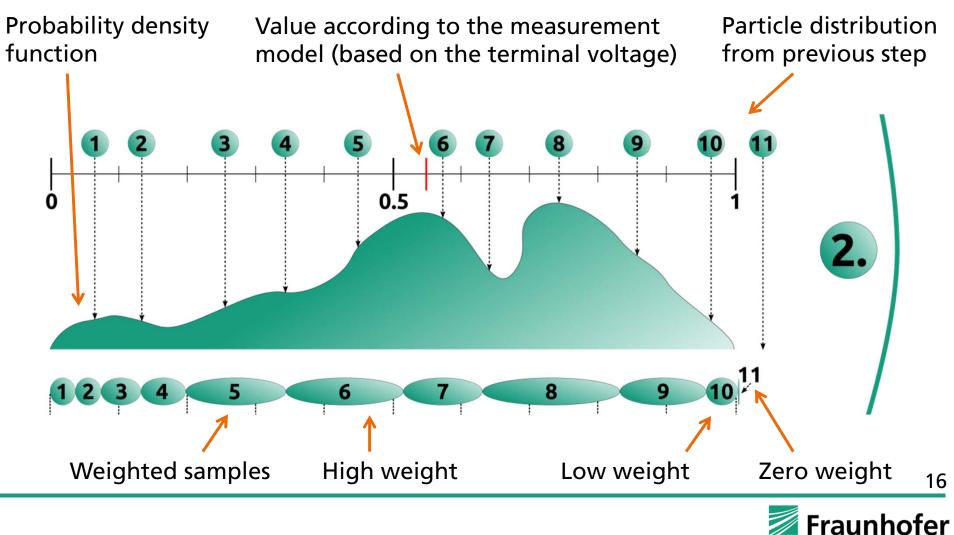


1. Step: Use of the process model, diffusion

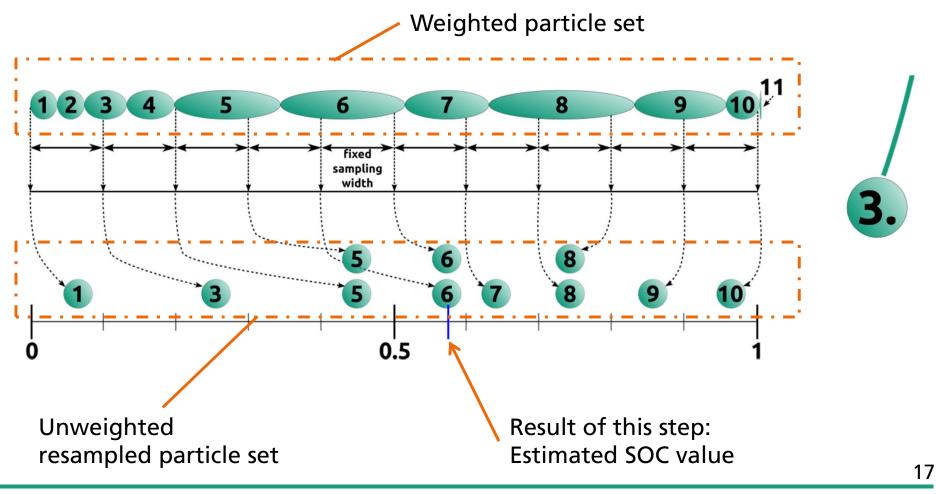




#### 2. Step: Use of the measurement model, weighting

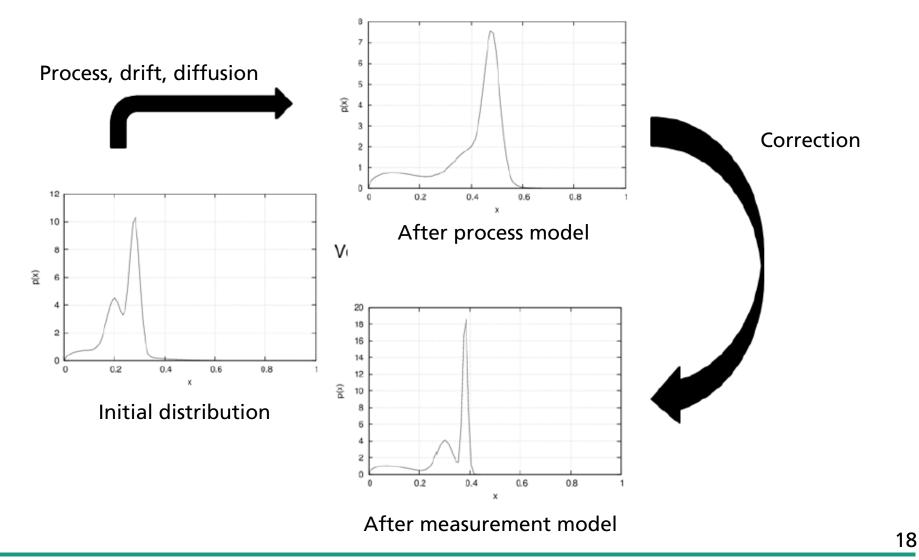


3. Step: Low variance resampling



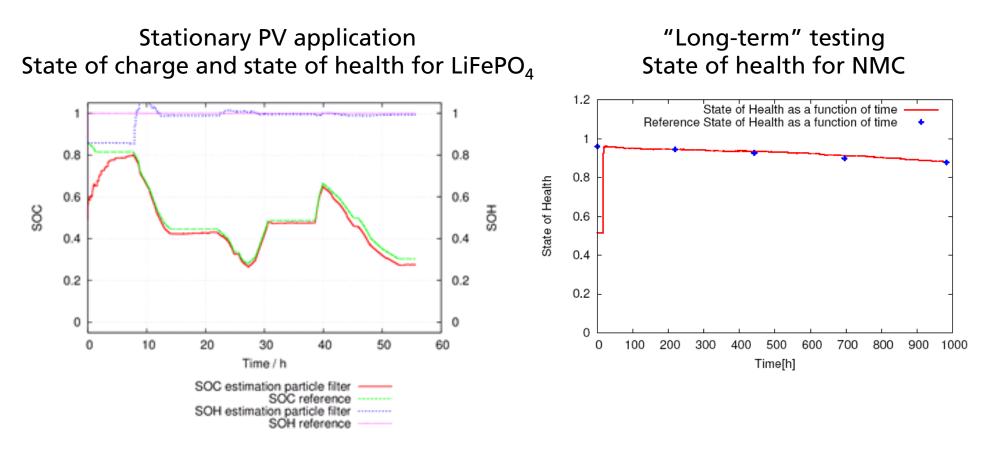


## Particle filter Evolution of probability density function





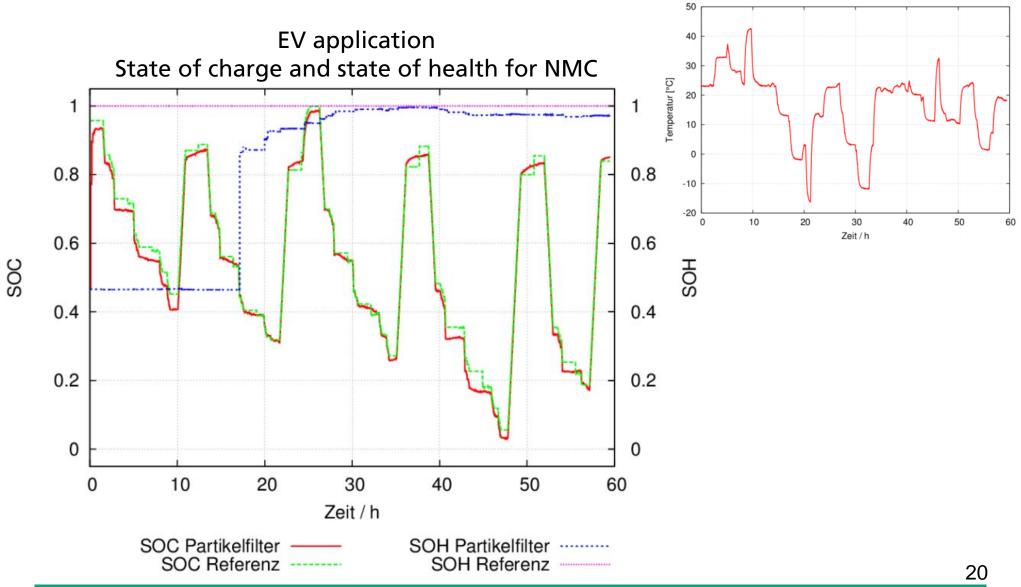
#### Particle filter Results





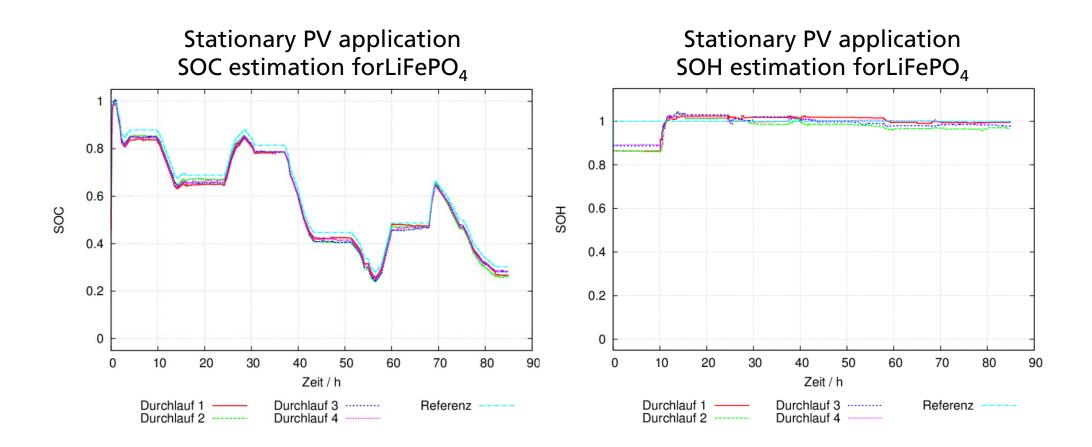
## **Particle filter Results**

Imposed temperature





#### **Particle filter Results – Filter noise**





#### Conclusions

- State of charge and state of health estimation very important but also sophisticated task for *nearly* all battery applications
- Particle filter for state of charge and state of health estimation with the following features:
  - Precision: Finds "true" value with minimal variation
  - > **Speed:** Sufficiently fast to cope with PV as well as EV profiles
  - > Flexibility: Able to cope with different initial values and temperature profiles
- Due to low computational efforts it can be implemented very well on small scale microcontrollers of battery management systems
- $\rightarrow$  Particle filter is a very flexible and reliable tool for estimating inner states of batteries





